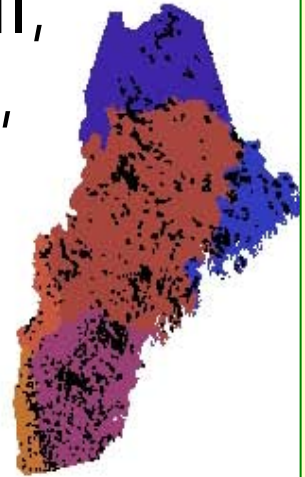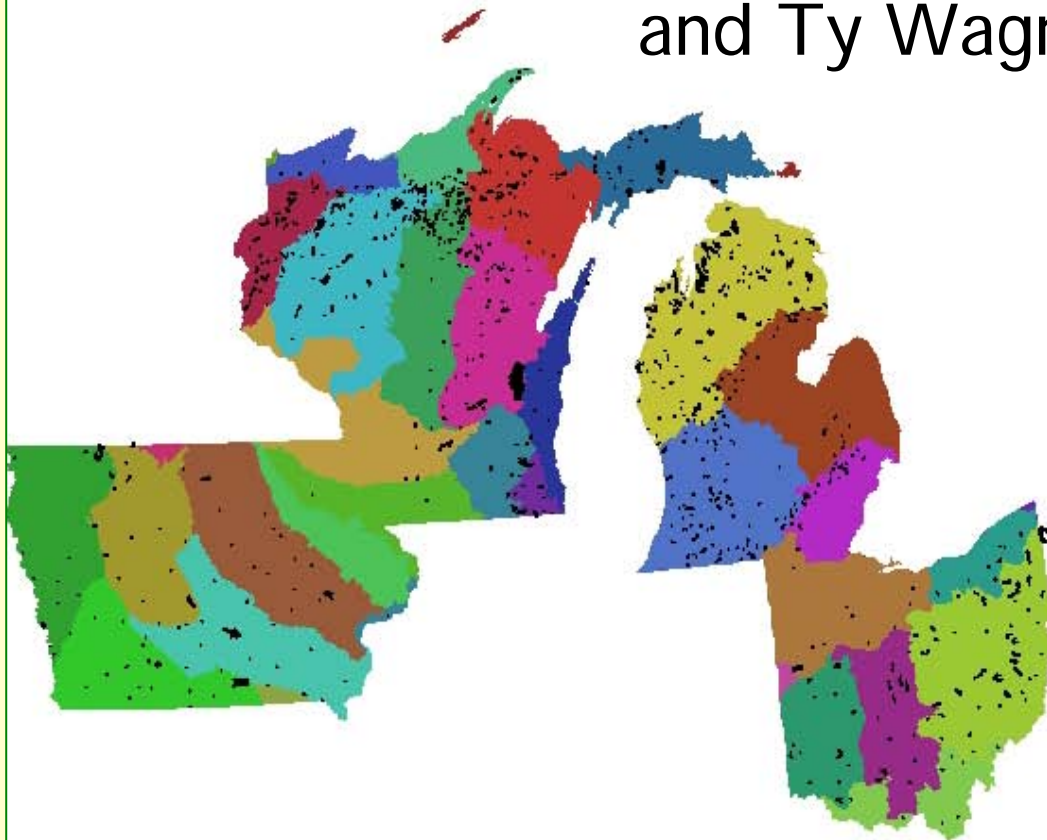# A Hydrogeomorphic Lake Classification System for Lake Assessment

Mary T. Bremigan, Kendra Spence Cheruvelil, Patricia A. Soranno, Katherine E. Webster, and Ty Wagner

Outline

1) Project Overview

2) Grouping Lakes: Statistical Comparison of Regionalizations

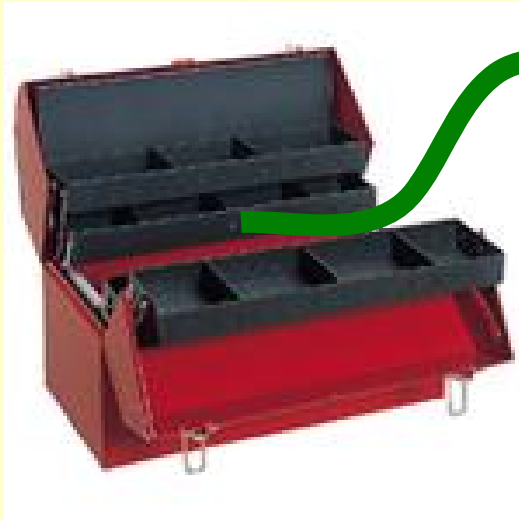3) Detecting Trends: Quantifying Variance Components

Overview: Project Workshop

November 2005

Overview: Project Goals

1) to develop a robust and widely applicable lake classification system

2) to build a lake assessment toolbox for state and national needs

- Lake reference conditions
- Bioassessment indicators
- Biological condition gradients
- Data gaps in sample designs

Project Overview

1. Assemble lake data from six states.

2. Statistically test alternative 'regionalization frames'.

3. Develop & test the *HydroGeomorphic Lake Classification framework (HGLC)*.

4. Build a lake assessment toolbox within the HGLC framework.

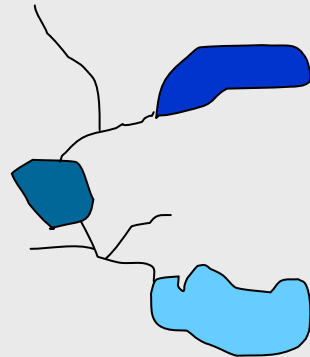Hydrogeomorphic (HGM) effects on lakes:
a hierarchical approach.
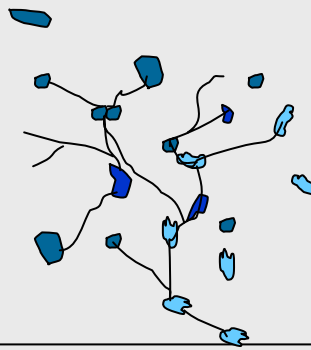
Regional
(climate, geology)

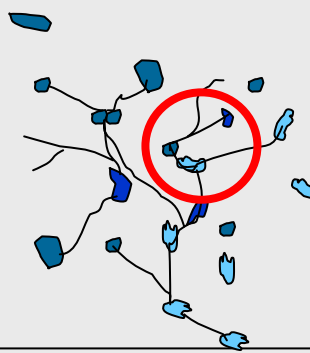HGM effects on lakes: a hierarchical approach.
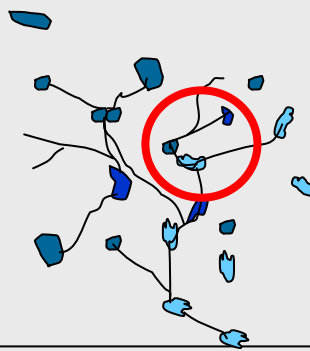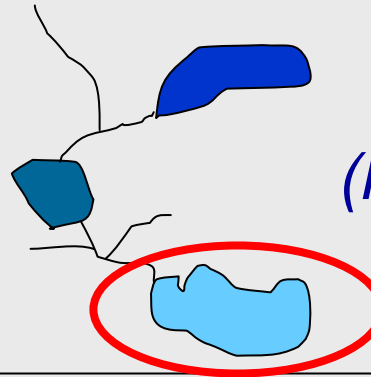

Regional
(climate, geology)
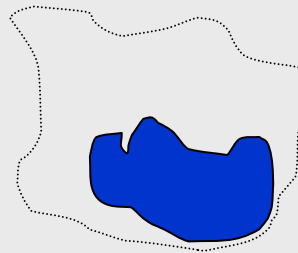
Sub-regional
(hydrologic connections)

HGM effects on lakes: a hierarchical approach.

Regional
(climate, geology)

Sub-regional
(hydrologic connections)

Local: watershed
(catchment area, land use)
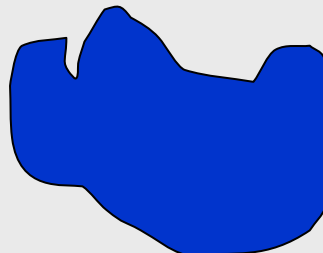
Local:lake
(lake size and depth)

Overview: Lake Assessment Toolbox
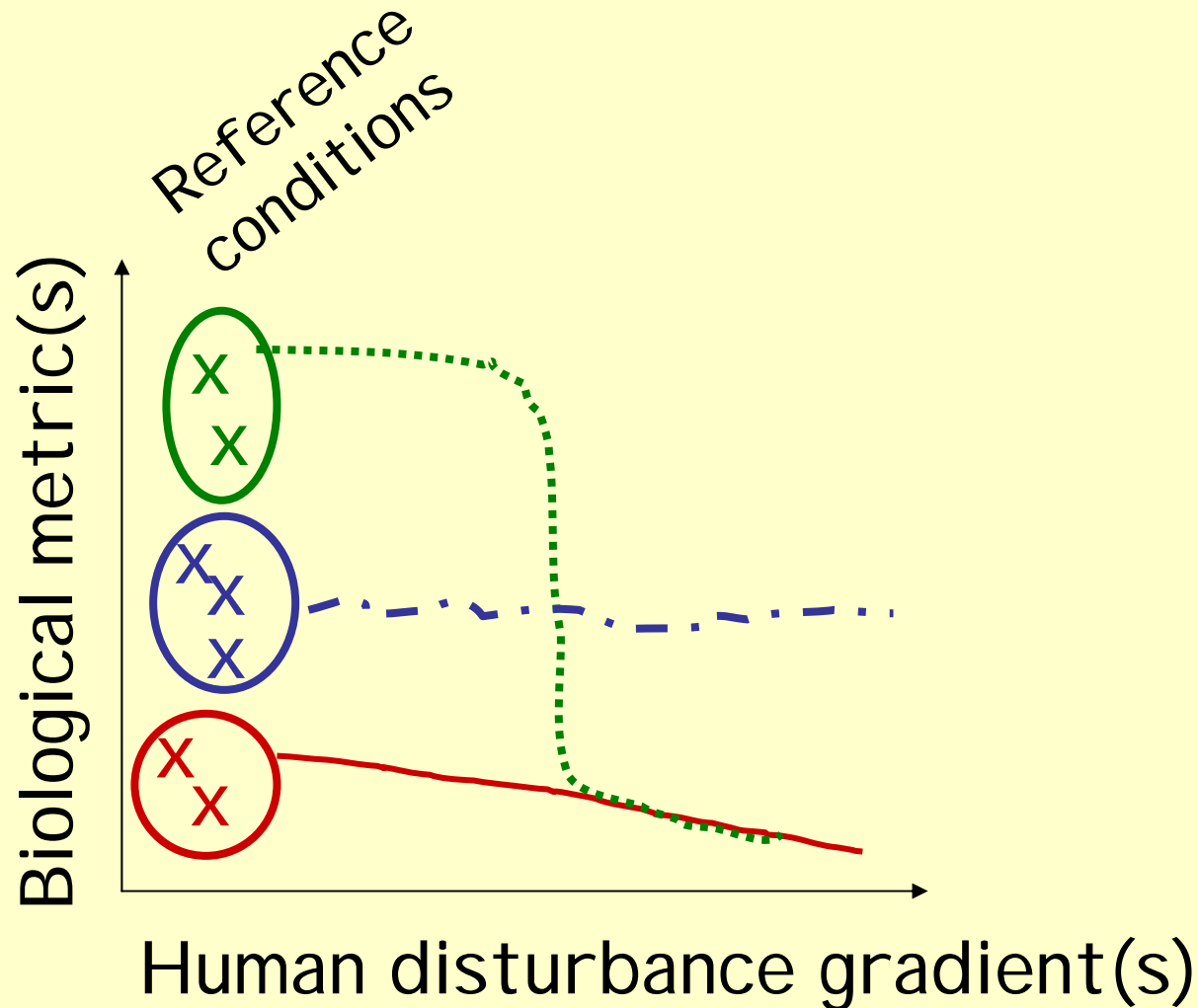
Grouping Lakes:
Statistical Comparison of Regionalizations

REGIONALIZATION = a classification approach that groups together water bodies that lie within a similar geographical region (Seelbach *et al.* 2002)

- *e.g.*, ecoregions or major river catchments

- If regionalizations "capture" substantial variation among lakes, then they can be a useful component of assessment frameworks.

- Regionalization is the first step in developing the HGLC classification.

Regionalizations and Hierarchical Linear Models
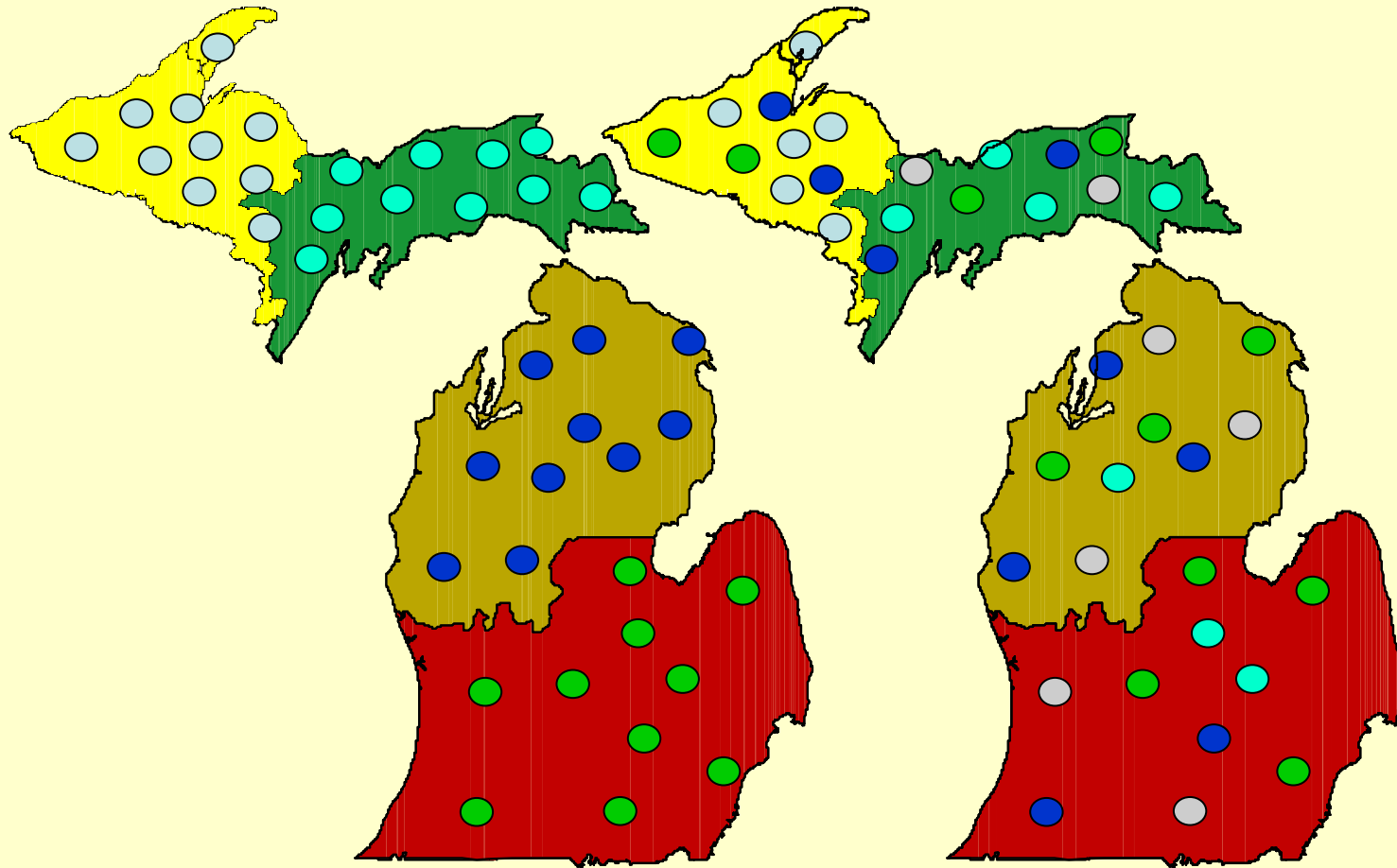
among region variation   v. high   low

within region variation   v. low   high

Regionalizations: Statistical Analysis

$$Y_{ij} = \gamma_{00} + u_{0j} + r_{ij}$$

$$u_{0j} \sim N(0, \tau_{00})$$ $$r_{ij} \sim N(0, \sigma^2)$$

% variation among regions = $\dfrac{\tau_{00}}{\tau_{00} + \sigma^2}$

Best regionalization framework criteria:

1) Largest % variation among regions

2) Smallest AIC_c (model fit statistic)

Lakes and Regionalizations

2314 lakes from 6 states (IA, WI, MI, OH, NH, ME)
- **Lake : $\geq$ 1 ha surface area and maximum depth $\geq$ 2 meters, includes (dammed and undammed) and reservoirs**
- **Average lake area:** 2812 ha (range: 13.3–533,666 ha)
- **Average maximum depth:** 11.7 m (range: 2–96.3 m)

11 regionalization frameworks (regions, subregions)
- **Political boundaries:** State, county
- **Terrestrially derived ecoregions:** EPA regions (agglomerated Omernik), Omernik level 3 ecoregions, Bailey sections, Major Landscape Resource Areas
- **Aquatically derived ecoregions:** Freshwater Ecoregions, Ecological Drainage Units, Hydrologic Landscape Regions, 6 digits hydrologic units, 8 digit hydrologic units

8 Water Quality Response Variables
(n, average, range)

Total nutrients (ug/L):
- TP (2314, 22, 1–920)
- TN (1466, 686, 66–14,661)

Algae: Chlorophyll (2314, 10, 0.02–328 ug/L)

Water clarity: Secchi disk depth (2314, 3.6, 0.2–14.3 m)

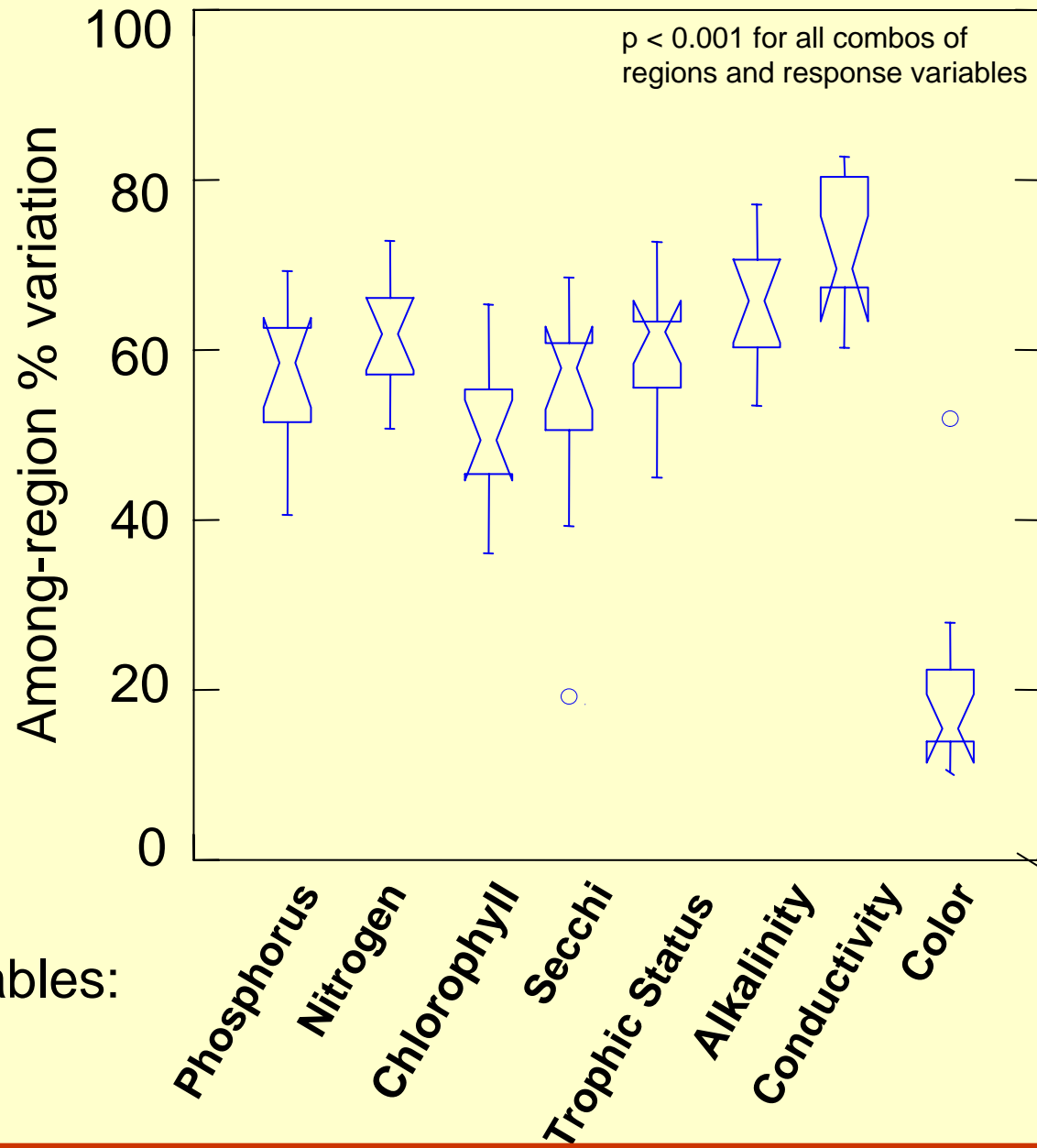**Trophic status:** PCA factor scores of TP, chl, & Secchi (2316)

Acid buffering capacity:
- Alkalinity (1970, 45, -2–302 mg/L CaCO3)
- Conductivity (1667, 124, 10–1313 uS/cm)

Water color:
- Water color (1650, 24, 1–193 PtCo)

Results: Regionalization Matters

p < 0.001 for all combos of regions and response variables

Among-region % variation

Response Variables:
Phosphorus, Nitrogen, Chlorophyll, Secchi, Trophic Status, Alkalinity, Conductivity, Color

Cheruvelil et al. in prep.

Results: Which Regionalization Is Best?

Criteria 1) highest regional % variation

# regions:	6	370	18	4	29	33	8	45	17	57	231
	State	**County**	**Omernik L3**	**EPA**	**Bailey Section**	**MLRA**	**FW Ecos**	**EDU**	**HLR**	**HU-6**	**HU-8**
Phosphorus						X					
Nitrogen											X
Chlorophyll						X					
Secchi		X									
Trophic Status		X									
Alkalinity						X					
Conductivity											X
Color						X					

Political (State, County)   **Terrestrial** (Omernik L3, EPA, Bailey Section, MLRA)   **Aquatic** (FW Ecos, EDU, HLR, HU-6, HU-8)

Results: Which Regionalization Is Best?

Criteria 2) Practicality: lowest AICC

# regions:	6	370	18	4	29	33	8	45	17	57	231
	State	County	Omernik L3	EPA	Bailey Section	MLRA	FW Ecos	EDU	HLR	HU-6	HU-8
Phosphorus						X X					
Nitrogen					X						X
Chlorophyll						X X					
Secchi	X	X									
Trophic Status		X				X					
Alkalinity						X				X	
Conductivity						X					X
Color	X	X				X					X

Political — State, County

Terrestrial — Omernik L3, EPA, Bailey Section, MLRA

Aquatic — FW Ecos, EDU, HLR, HU-6, HU-8

Regionalizations: Conclusions to Date

Regionalization matters.

- % variation among regions ranged 40-70% for most response variables.

- There is not a single best regionalization for all water chemistry measures.

- Land use differences may obscure the 'natural HGM signature'.

Regionalization to Variance Components

- Regionalization plays a role in assessing current status, and also in detecting trends over time.

- The ability of a monitoring program to detect trends over time is influenced by spatial variation.

- Several other sources of variation also play a role. Hence, it's important to consider the 'components of variance' when selecting response metrics and designing monitoring systems.

Components of Variance

Advocated for addressing status and trends of ecological data (Urquhart *et al.* 1998)

– Partition total variance into:

- Site-to-site (spatial) variation
- Coherent temporal variation (i.e., synchrony) – affects all sites in a similar manner
- Ephemeral temporal variation – independent yearly variation at each site (site×year)
- Random slope – each site allowed to have own trend
- Residual variation – unexplained error

Components of Variance

Provides insight:

- What variables are good indicators of temporal trends?
    - e.g., variables with large coherent temporal variation are poor indicators
- What aspects of the monitoring design can be changed to increase the power to detect trends?
   - e.g., ephemeral temporal variation can be reduced by sampling more sites (lakes) per year

Variance Components: Analyses

Step 1: We used a weighted mixed model to estimate components of variance and determine if there was a trend over time in size at age for: 6 fish species, 2 age classes, and 2 states.
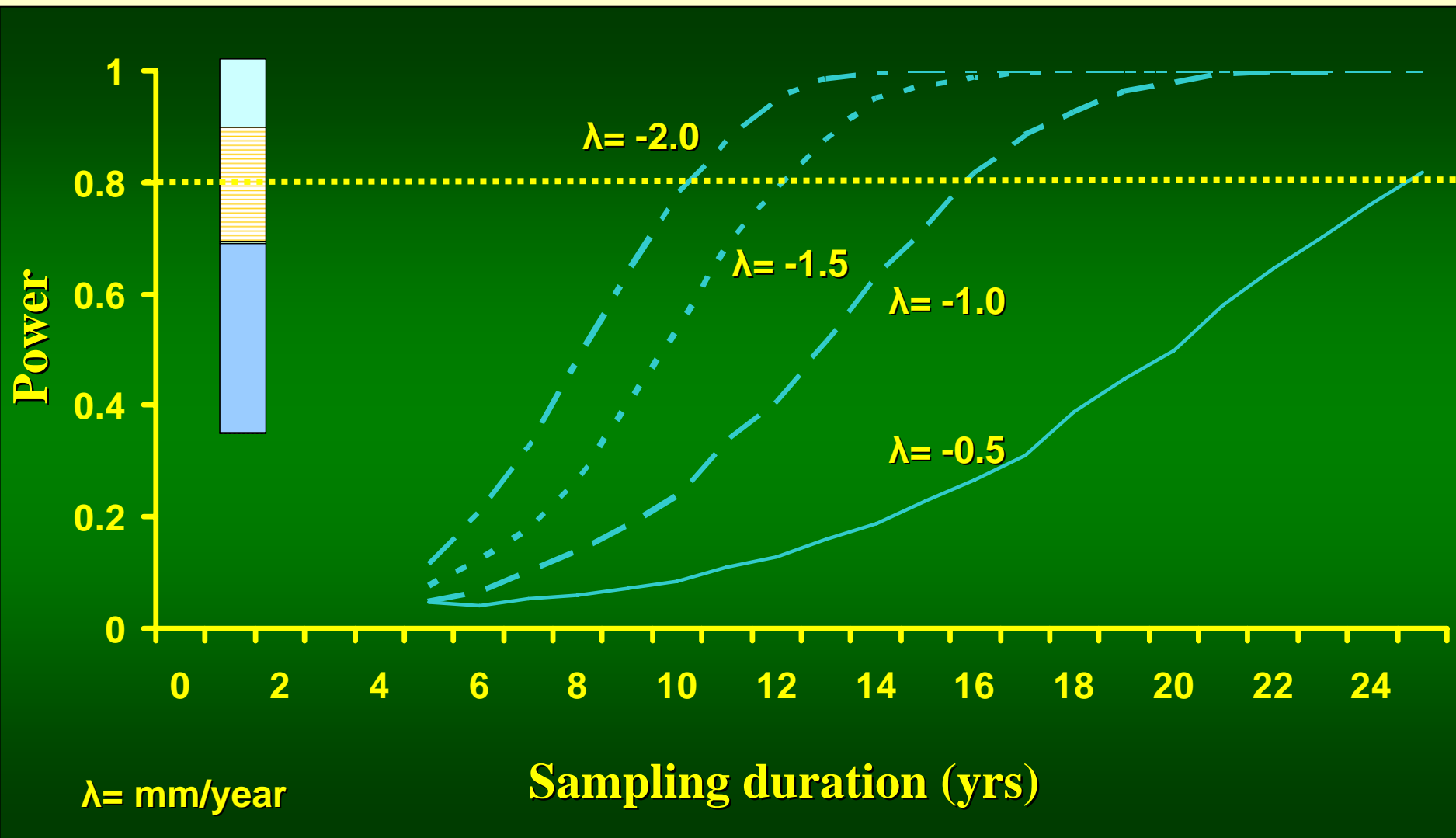
Step 2: We selected 2 situations with very different variance components and used simulation modeling to explore effects of variance components and monitoring design on the statistical power to detect a trend over time.
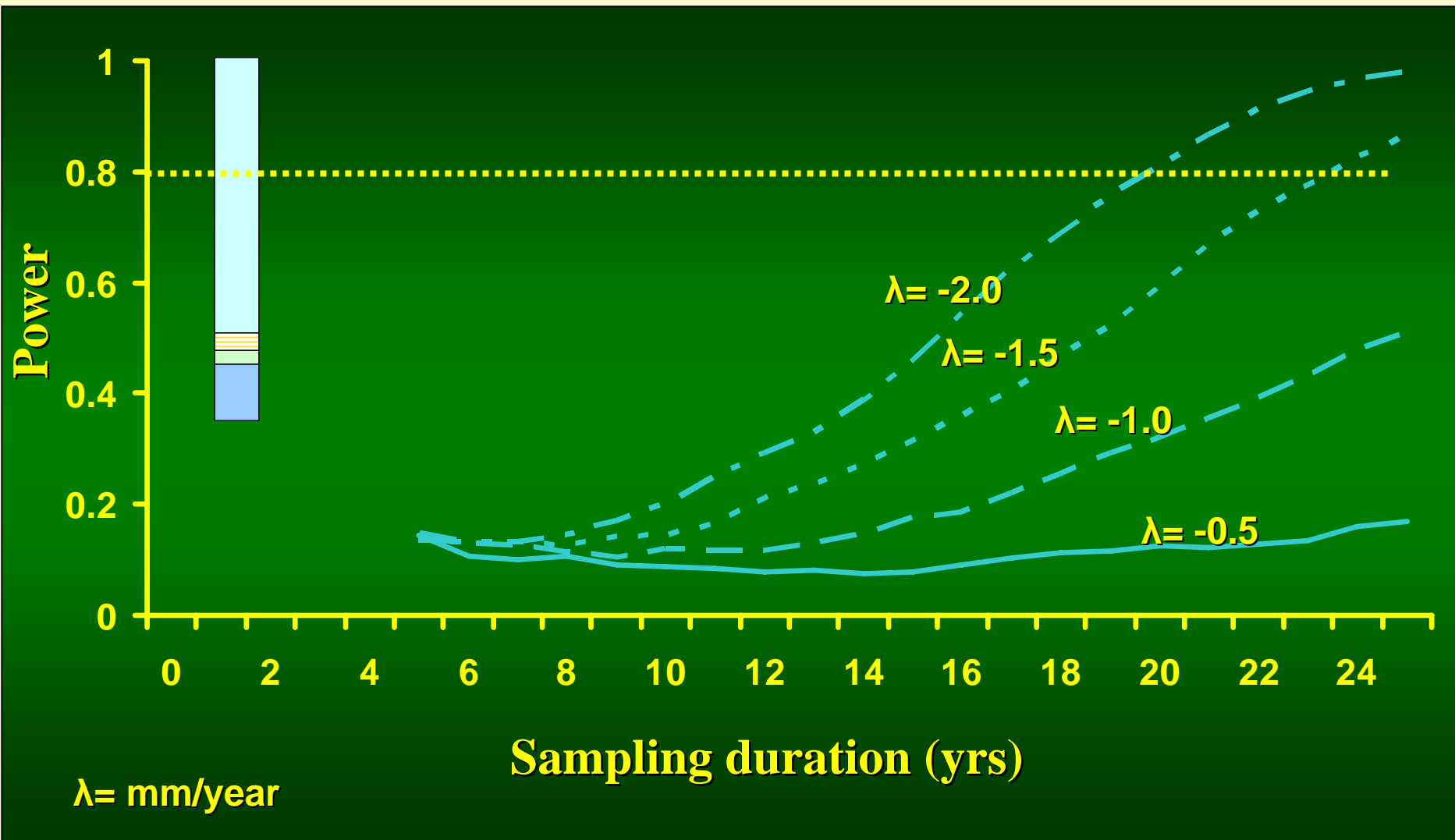
Variance Components: Results

Wagner et al. in prep
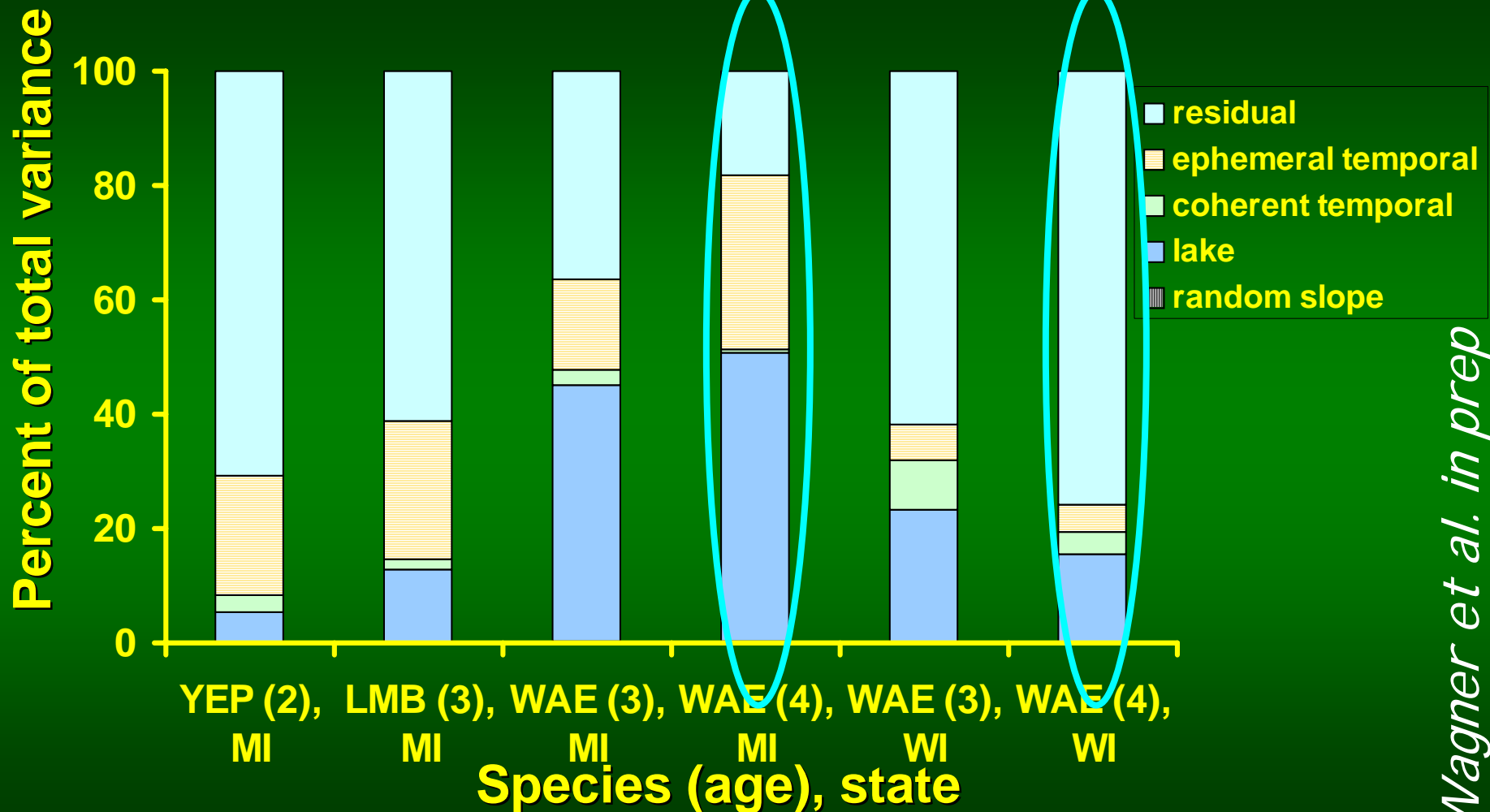
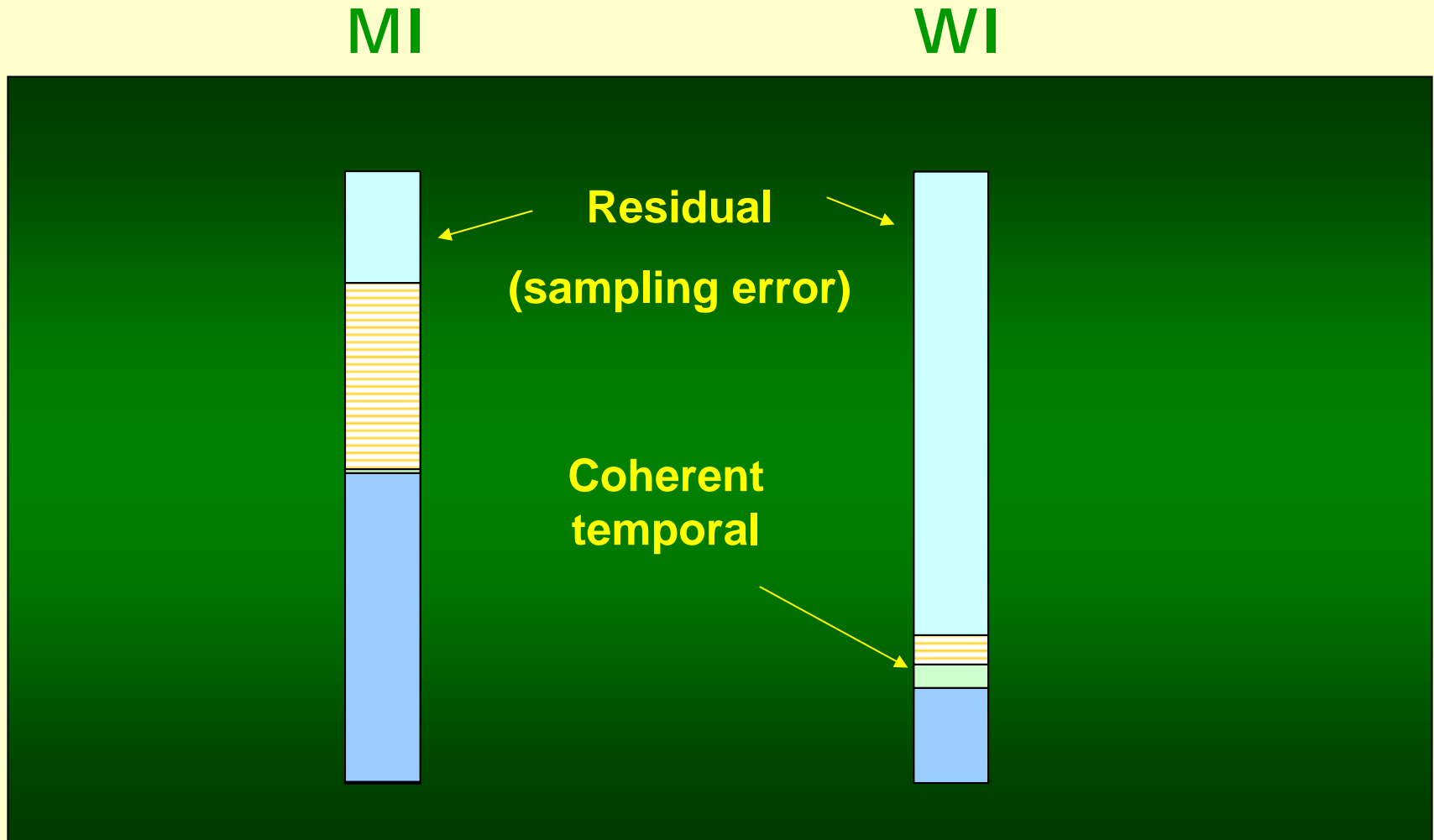# Variance Components: Simulations
Power depends on trend magnitude, but is lower overall for WI age 4 walleye.

λ= -2.0

λ= -1.5

λ= -1.0

λ= -0.5

Power

Sampling duration (yrs)

λ= mm/year

Variance Components: Simulations

Coherent temporal variation reduces power in WI.
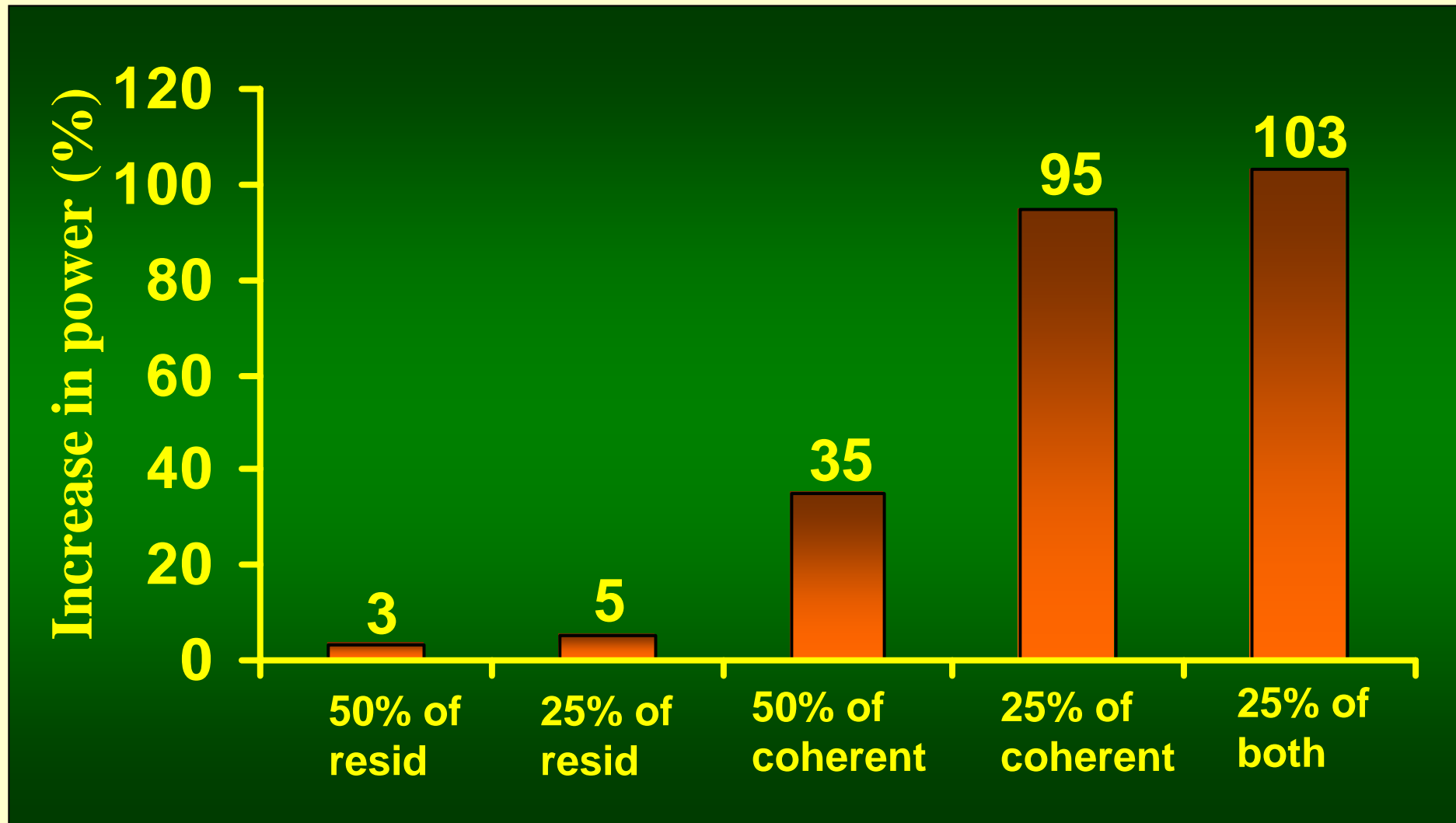
Variance Components: Conclusions to Date

- 🐸 Partitioning of variance components will differ among states (to an unknown degree).

- 🐸 Relatively small differences in coherent temporal variation have large implications for power to detect temporal trends.

Conclusions, Constraints, and Directions

- Variation captured by regionalizations varies among water chemistry metrics and frameworks.

- Current land-use patterns likely underlie MLRA's 'success.' Future analyses will focus on least disturbed lakes.

- Quantifying variance components for several lake metrics and across spatial scales will be important for assessing the statistical power of a national survey of lakes.

- Landscape and lake data compilation across states is never-ending, time consuming, and requires $.

MSU EPA–NLAPP Project Participants

Iowa: John Downing (Iowa State University)

Maine: Katherine Webster, Peter Vaux, Kathleen Bell (University of Maine), Linda Bacon (ME-Dept. Environmental Protection)

Michigan: Patricia Soranno, Mary Bremigan, Kendra Spence Cheruvelil, Jan Stevenson, Howard Wandell, Ty Wagner, Sherry Martin (Michigan State University), Ralph Bednarz, Sarah Holden, Sylvia Heaton (MI-Dept.Environmental Quality), Kevin Wehrly (MI-Dept. Natural Resources), Amy Derosier (MI-Natural Features Inventory)

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Ohio: Bill Renwick, Mike Vanni, Maria Gonzalez (Miami University), Jeff DeShon, Robert Davic (OH EPA Surface Water)

Wisconsin: Paul Garrison, Nancy Nate, Tim Asplund, Jennifer Filbert (WI-Dept. Natural Resources)